A FRAMEWORK FOR INTEGRATED TRACKING AND DISCRIMINATION

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ABSTRACT

The Decisive Analytics Corporation (DAC) team describes a framework to fully integrate the tracking and discrimination processes in the Ballistic Missile Defense System (BMDS).

1. INTRODUCTION

The contributions developed under this work center on fully integrating the tracking and discrimination processes in the Ballistic Missile Defense System (BMDS). The current architecture of the BMDS artificially separates the tracking and discrimination algorithms. Each model exists independently with no ability to influence the operation of the other. This situation precludes taking advantage of the inherent relationships that exist between a threat object's type and its kinematics. Making full use of these relationships will improve both the accuracy of the tracking algorithm and the power of the discrimination model to distinguish the Reentry Vehicle (RV) from other, non lethal object types. This framework could be equally viable to Army Air and Missile Defense on Tactical Ballistic Missiles (TBM) and maneuvering Air Breathing Targets (ABT) by using kinematics as well as geometry to continue a track after it leaves and returns to the field of view. To enable this integration, the key contributions developed under this effort include:

1. An implementation of a novel, hybrid, dynamic Bayesian Network inference algorithm and modeling language capable of representing discrete and continuous variables,
2. An integrated tracking and discrimination solution we achieved through a single Bayesian network model, and
3. A Multi-Hypothesis Bayesian Network (MHBN) technique that improves track correlation by managing and merging prior beliefs with new tracking and discrimination measurements.

2. INFERENCE ALGORITHM

A cornerstone accomplishment of this SBIR was the development and implementation of a Bayesian inference algorithm suitable for use with hybrid, dynamic network models. The DAC team began with an implementation of a hybrid inference algorithm developed under a separate MDA-funded effort and added a dynamic capability. This algorithm represents systems with discrete and continuous variables (i.e. *hybrid*) as a possibly-large, yet structured Gaussian mixture models. A small example of a static hybrid network and its mixture representation is shown below in Figure 1.

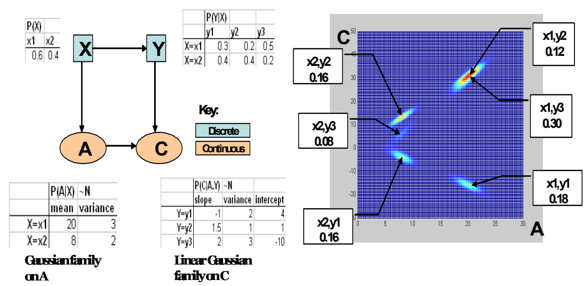

Fig. 1 - A static, hybrid Bayesian network and a plot of its corresponding Gaussian mixture.

Through the work completed on this SBIR, the algorithm can now work with two time step representations of dynamic Bayesian networks. A small example network and its resulting Gaussian mixture are shown below in Figure 2.

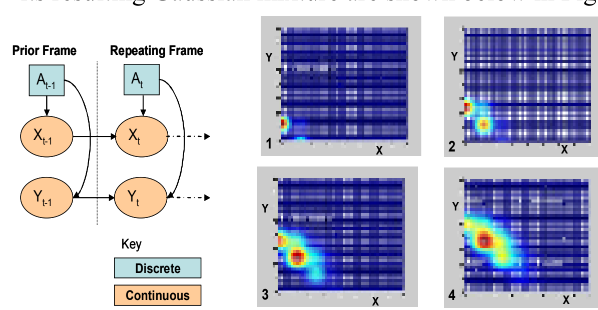

Fig. 2 - A two time step, dynamic, hybrid Bayesian network and a plot of its corresponding evolving distribution.

The algorithm makes use of several innovative techniques for managing state space explosions within a time slice and between time slices as the network evolves. These techniques include a means to efficiently enumerate the top most likely instantiations and corresponding Gaussian components in the network mixture and a collapsing algorithm approximation to identify and combine similar Gaussians as the network mixture is propagated forward in

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **01 DEC 2008**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**
4. TITLE AND SUBTITLE **A Framework For Integrated Tracking And Discrimination**		5a. CONTRACT NUMBER
		5b. GRANT NUMBER
		5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER
		5e. TASK NUMBER
		5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Decisive Analytics Corporation Arlington, VA, 22202**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR’S ACRONYM(S)
		11. SPONSOR/MONITOR’S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release, distribution unlimited**		
13. SUPPLEMENTARY NOTES **See also ADM002187. Proceedings of the Army Science Conference (26th) Held in Orlando, Florida on 1-4 December 2008, The original document contains color images.**		
14. ABSTRACT		
15. SUBJECT TERMS		

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**4**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

time. Furthermore, to perform hybrid inference, the algorithm makes use of closed-form mechanics for marginalizing and conditioning on evidence when linear Gaussian relationships exist and an unscented transform (a numerical integration technique) to provide the best Gaussian approximation when modeling nonlinear relationships between continuous parent and child variables.

3. INTEGRATED TRACKING AND DISCRIMINATION

Through this research, we have expressed the tracking and discrimination functions within a single, unified model and used our hybrid, dynamic Bayesian inference algorithm to solve it. This is depicted in Figure 3.

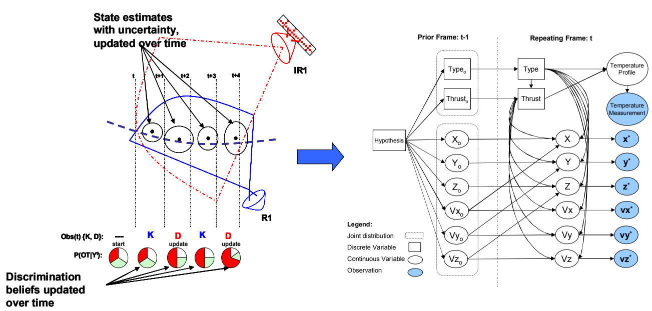

Fig 3 - Representation of multi-sensor tracking and discrimination within a single network model.

The two time step, hybrid, dynamic Bayesian network shown in Figure 3 models an object being tracked and discriminated as it moves in three dimensions with a switching behavior, randomly coasting or thrusting at any time. Here we consider that the object can only be one of two possible object types (1 or 2), with each type having its own unique temperature profile depending on whether it is currently thrusting or coasting. As the graphic in Figure 3 illustrates, we have simulated a situation where a radar is available for tracking the object and an IR sensor can be tasked to perform discrimination.

Using this integrated tracking and discrimination network, a truth model was generated for object type 2, along with a sequence of simulated kinematic and position measurements, with each measurement created with a random draw from the sensor error model distributions. The measurements were then applied to the hybrid, dynamic Bayesian inference algorithm developed under this effort to produce a sequence of filtered state estimates for the system as well as a sequence of posterior beliefs on object type. A key objective of the work completed under this effort was to demonstrate what improvements in discrimination performance can be expected as a result of expressing the tracking and discrimination in a common mathematical language. To accomplish this goal, the DAC team constructed a "discrimination-only" network model by extracting the discrimination variables from the network depicted in Figure 3. Using the same sequence of simulated temperature measurements created for the integrated tracking and discrimination experiment, the DAC team created a time series of object type beliefs using the stand-alone discrimination network. This series of discrimination-only object type beliefs is shown plotted along with the beliefs from the integrated tracking-discrimination model in Figure 4.

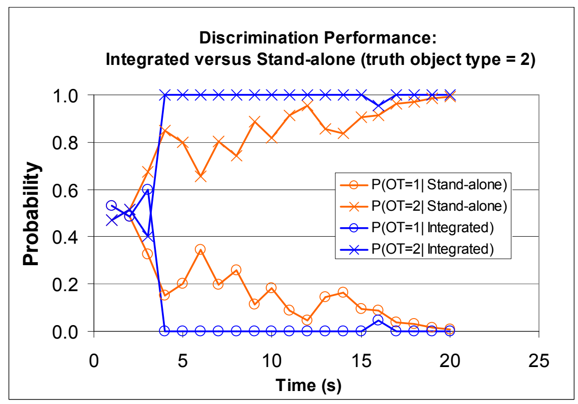

Fig. 4 - Kinematic differences in object type are exploited in the integrated model, improving the rate of discrimination.

As the plot illustrates, the combined discrimination and tracking model is able to discriminate the correct object type with near certainty by time step 5. As expected, the stand-alone discrimination model converges to the correct solution as well, albeit at a much slower rate. While the example network we have used for this comparison does not employ real sensor data or ballistic motion models, these results are quite promising nonetheless.

4. MULTIPLE HYOPOTHESIS BAYESIAN NETWORK TRACK CORRELATION

With an integrated network representation of tracking and discrimination, it is possible to apply the concepts of Multiple Hypothesis Bayesian Networks (MHBN) to the track correlation problem. Here, we assume a situation where strong posterior beliefs on type have been established for two objects that are being tracked. For external reasons, the system is unable to collect against these two objects for a period of time, after which two new local tracks are established. At this point, there is uncertainty about the correlation of the new local tracks with the existing system tracks. The use of MHBN to manage each of the possible pairings of local-to-system tracks is a natural extension of the integrated tracking and discrimination network. Because there is a single Bayesian network representation of the

existing system tracks for each object (prior to the sensor coverage gap), we can compute the likelihood of new, local measurements, given our previous beliefs on object type and forward-propagated kinematic state.

To test this concept, the DAC team generated two truth models, one with object type 1 and the second with object type 2. For this exercise, the object types were endowed with identical thrust-coast kinematic motion models and differed only in the temperature profile distributions used for discrimination. In this way, the MHBN track correlation technique could be evaluated with and without discrimination information, providing another opportunity to quantify the benefits of integrated tracking and discrimination. For each object, a time sequence of sensor measurements was simulated, with each observation drawn from the sensors' measurement error distributions. Using our hybrid, dynamic inference algorithm, we performed combined filtering and discrimination using these measurements for each track, up to a predefined point at which time a sensor coverage gap was simulated. After a number of seconds, the combined filtering and inference process started again, simulating the return of sensor coverage, using each track's forward propagated network. Because the truth models were created to intersect there is a great deal of overlapping uncertainty in each track's predicted kinematic state estimate after the coverage gap. For three time steps after the return of coverage, we evaluated the likelihood of a (now-local) measurement having come from each of our existing (system) track network models. Finally, as previously stated, we performed this entire experiment twice; once only using kinematic measurements to evaluate hypothesis likelihoods and again using kinematic and discrimination measurements to evaluate hypotheses. The results of both versions of the experiment are shown in Figure 5.

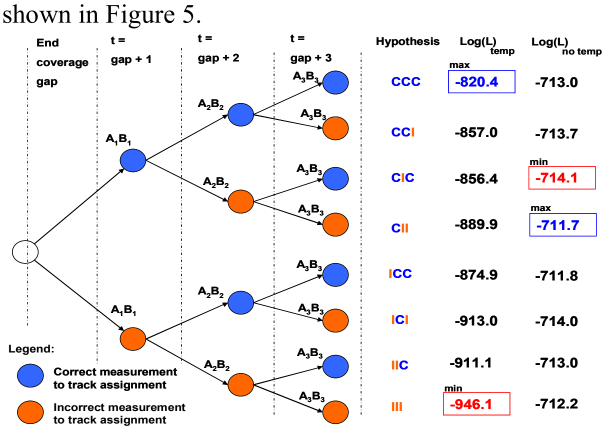

Fig 5 - Discrimination information disambiguates overlapping kinematics after a sensor coverage gap.

As Figure 5 shows, the correct measurement to track assignment hypothesis "CCC" across all three time steps is the most likely hypothesis when discrimination measurements are used along with kinematic measurements. However, the same correct hypothesis is not scored as most likely when we omit the discrimination measurement. Rather, we see that hypothesis "CII" is calculated to be the most likely without discrimination. Also, there is very little difference between the likelihoods of any hypothesis in this case. This result demonstrates the power of combining discrimination information with tracking measurements, as a unique discrimination signature can help to disambiguate cloudy kinematic state estimates.

5. ONGOING RESEARCH

Recent efforts have centered on extending the capabilities of the inference algorithm and modeling language to support the development of a high-fidelity, single sensor network model for tracking and discriminating an object in ballistic motion. These have included an extension of the inference algorithm's unscented transform numerical integration facilities to accommodate vector-valued functions, and a modification to the algorithm's XML modeling language to express the notion of network variables with distributions given by a general system of equations. These steps enabled us to implement a differential equation solver to propagate the ballistic filter forward in time and embed the filter directly in the network via an XML file for a six state ballistic filter with a spherical-to-Cartesian measurement error model for a single sensor. We have also developed a test-bed environment to test the performance of the ballistic filter network model with noisy, simulated radar measurements collected against a ballistic truth model. The ballistic filter network model is shown in Figure 6.

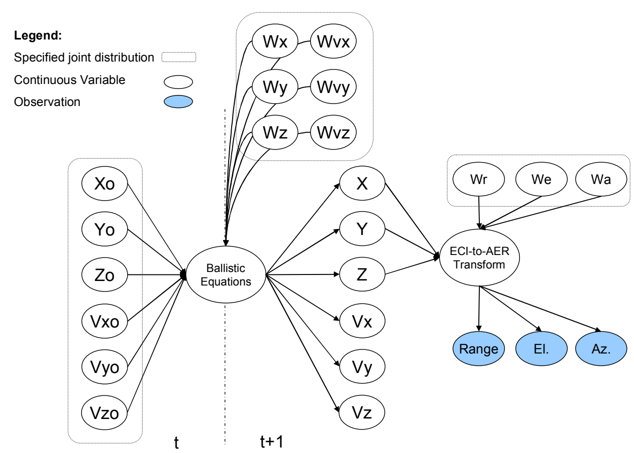

Fig. 6 – A network model representation of the unscented, six state ballistic filter.

CONCLUSIONS

The unified tracking and discrimination framework presented here shows promise to improve the rate of object type discrimination by making use of relationships that exist between an object's type and its kinematics. The warfighter would benefit from this innovation through a reduction in the sensor resources required for positive discrimination of object type, allowing for more effective allocation of sensors during an engagement. This framework also provides for a robust track correlation technique to help disambiguate overlapping kinematic state estimates in high target density situations.

ACKNOWLEDGEMENTS

We would like to acknowledge and thank SMDC and the MDA Small Business Innovative Research Program Office for their support and funding of this research.